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Abstract

Forecasting food prices is an important component of the U.S. Department of Agriculture's short-term outlook and long-term baseline forecasting activities. A food price-forecasting model is developed by applying an inverse demand system, in which prices are functions of quantities of food use and income. Therefore, these quantity and income variables can be used as explanatory variables for food price changes. The empirical model provides an effective instrument for forecasting consumer price indexes of 16 food categories.

Keywords: Food price forecasts, inverse demand system, autoregressive model.

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Summary

A food price-forecasting model is developed to provide information about how changes in the quantities of food use affect consumer food prices. The model specification explicitly recognizes that lags between farmers' decisions on production and commodities marketed may predetermine quantities, with price adjustments providing the market-clearing mechanism. This model, by incorporating economic rationale specification, is an alternative approach to the commonly used time series model for food price forecasts. The empirical model, represented by a set of price equations with estimates expressed as price flexibilities, provides an effective instrument for forecasting consumer price indexes of 16 food categories by using 6 aggregate food quantities as input information.

According to the model estimates, for example, a marginal 1-percent increase in the quantity of red meats would result in price decreases of 0.91 percent for beef, 1.42 percent for pork, and 0.27 percent for other meats. On the other hand, a marginal 1-percent increase in the quantity of poultry would result in a price decrease of 0.84 percent for poultry. Regarding the cross-quantity effects, an estimated cross-price flexibility between two food categories shows the percentage change in the amount consumers are willing to pay for one food when the quantity of another food increases by 1 percent. For example, the cross-price flexibility of poultry with respect to the quantity change of red meats is -0.40 percent, and the cross-price flexibilities of beef, pork, and other meats with respect to the quantity change of poultry are -0.15, -1.03, and -0.42 percent. The negative values of these cross-price flexibilities suggest that red meats and poultry are substitutes.

Regarding forecasting capability of the model, the estimates of goodness of fit (R^2) in each price equation are satisfactory. All estimates of R^2 are higher than 0.91, and in 14 of 16 cases, R^2 is higher than 0.95. Also, in the simulation over the sample period, the measures of root-mean-square errors as a percent of sample mean are in a range between 0.37 and 1.98 percent, indicating that the conformity of the fitted prices with the sample observations appears reasonably good. These statistical results suggest that the estimated inverse demand model alone can be used for price forecasts.

Finally, a spreadsheet model for forecasting consumer food prices was developed that users can easily implement for timely outlook and market analysis. For conducting forecasting, one may use the prior information on quantities of food use and per capita income to forecast food prices. For program analysis, one may assume various scenarios of changes in the prior information and then conduct simulation experiments for evaluation of the program effects. The accuracy of the forecasts of consumer food prices, however, depends on the reliability of prior information on quantities of food use and per capita income in the future.

Forecasting Consumer Price Indexes for Food

A Demand Model Approach

Kuo S. Huang

Introduction

Forecasting food prices is an important component of the U.S. Department of Agriculture's short-term outlook and long-term baseline forecasting activities. A food price-forecasting model is needed to provide information for use by agricultural policy decision-makers to evaluate the effects of changes in farm products due to farm programs, economic conditions, and weather on food prices. The objective of this report is to develop a price-forecasting model that can be easily implemented for timely outlook and situation analyses.

Some food price-forecasting models use a time series approach such as the Autoregressive Integrated Moving-Average (ARIMA) model in Box and Jenkins (1970). The time series model, which depicts the historical movement of time series data observations, is a convenient approach because it uses mainly its own price variable to predict food prices. Because none of the time series models incorporates economic rationale, however, the models' forecasts may be unreliable when there is a change in economic conditions.

To include economic reasoning in the food price forecasts, this study applies an inverse demand system, in which prices are functions of quantities and income. As indicated by Hicks (1956), the Marshallian demands have two functions: one shows the amounts consumers will take at given prices, and the other shows the prices at which consumers will buy at given quantities. The latter function, "quantity into price," is essentially what the inverse demand system expresses.

The inverse demand system is theoretically sound and has considerable appeal as applied to food price forecasting. It has been long recognized that lags between farmers' decisions on production and commodities marketed may predetermine quantities, with price adjustments providing the market-clearing mechanism. Therefore, quantities of food production and use are likely appropriate variables to use in food price forecasts. Hence, an inverse demand system for food price forecasts is capable of capturing the economic demand-pull factors, such as food use and income in the food-price movements.

The materials of this report are presented in two parts. At the beginning, the specification of a price-forecasting model is discussed. The major focus is on how to apply an inverse demand system for forecasting food prices. Then the empirical results of an estimated inverse demand system are presented.

A Price-Forecasting Model

In this section, a price-forecasting model is developed by applying an inverse demand system approach. Assuming that there are n goods in a demand system, let q denote an n-coordinate column vector of quantities demanded for a "representative" consumer, p an n-coordinate vector of the corresponding prices for the n goods, $m = p'q$ the consumer's expenditure, and $U(q)$ the utility function, which is assumed nondecreasing and quasi-concave in q. The primal function for maximizing consumer utility is the Lagrangian function:

$$\text{Maximize } L = U(q) - \lambda\,(p'q - m). \qquad (1)$$

By differentiating the Lagrangian function, the necessary conditions for optimums are

$$u_i\,(q) = \lambda\, p_i \qquad i = 1, 2, \ldots, n \qquad (2)$$

$$p'q = m \qquad (3)$$

in which $u_i\,(q)$ is the marginal utility of the ith good. In equation 2, λ is known as the marginal utility of income, showing the change in the maximized value of utility as income changes. This equation represents an equilibrium condition, in which each marginal utility divided by its price is equal (constant at λ) for all goods.

The inverse demand system can be obtained by eliminating the Lagrangian multiplier λ from the necessary conditions of equation 2. Multiplying both sides of equation 2 by q_i and summing over n goods to satisfy the budget constraint of equation 3, the Lagrangian multiplier is then obtained as

$$\lambda = \Sigma_j\, q_j\, u_j\,(q)\,/\,m \qquad j = 1, 2, .., n \qquad (4)$$

Substituting equation 4 into equation 2 yields the Hotelling-Wold identity, which defines the inverse demand system from a differentiable direct utility function as

$$p_i\,/\,m = u_i\,(q)\,/\,\Sigma_j\, q_j\, u_j\,(q) \qquad i, j = 1, 2, .., n \qquad (5)$$

in which $p_i\,/\,m$ is the normalized price of the ith commodity.

Equation 5 represents an inverse demand system in which the variation of price is a function of quantities demanded and is proportional to a change in income. For given quantities demanded, an increase in income will cause each commodity's price to increase at the same rate. Therefore, all income flexibilities are implicitly constrained to 1. This model has been applied in Huang (1991) for a 40-equation demand system consisting of 39 food categories and 1 nonfood sector.

On the choice of functional form for equation 5, the loglinear approximation of the Hotelling-Wold identity is used in this study for practical reasons. In addition to the linear model for easy estimation, the parameters of the loglinear form represent direct estimates of demand flexibilities. An annual statistical model for the ith price equation in terms of n quantities demanded is specified as follows:

$$\log\,(p_{i\,t}\,/\,m_t) = \alpha_i + \Sigma_j\, \beta_{i\,j}\,\log\,(q_{j\,t}) + v_{i\,t} \qquad i, j = 1, 2, .., n \qquad (6)$$

where variables at time t are $p_{i\,t}$ (price of ith commodity), m_t (per capita income), $q_{j\,t}$ (quantity demanded for jth commodity); $v_{i\,t}$'s are random disturbances.

Furthermore, according to Houck (1966) and Huang (1994), the price flexibilities of $\beta_{i\,j}$'s should be constrained by the following theoretical relationships:

$$\beta_{i\,j} = (w_j\,/\,w_i)\,\beta_{j\,i} - w_j\,(\Sigma_k\,\beta_{j\,k} - \Sigma_k\,\beta_{i\,k}) \qquad i, j, k = 1, 2, .., n \qquad (7)$$

where w_i is the expenditure share of the ith food category.

As suggested by Muth (1961), there is little empirical interest in assuming that the disturbance term in a structural model is completely unpredictable, and it is desirable to assume that part of the disturbance may be predicted from past observations. Because the expected values of the disturbance could be related to economic conditions prevailing in the past years, the disturbance is assumed to be not independent over time but to follow an autoregressive process.

Following Muth's suggestion, an autoregressive specification for the disturbance terms of the inverse demand system in equation 6 is applied in this study to enhance the price-forecasting capability. An autoregressive process of residuals lagged up to *l* years is specified as follows:

$$v_{i\,t} = \Sigma_h \gamma_{i\,h} v_{i\;\;t-h} + \varepsilon_{i\,t}$$
$$i = 1, 2, .., n; \;\; h = 1, 2, .., l \qquad (8)$$

where $\varepsilon_{i\,t}$'s are random disturbances in which $\varepsilon_{i\,t}$ is assumed to be identical normal and independently distributed as $\varepsilon_{i\,t} \sim IN(0, \delta^2 I)$, and $v_{i\,t}$ is assumed to be serially correlated.

In the following empirical application, a structural component model of equation 6 is estimated. In addition, for an improvement in forecasting performance, an autoregressive model is estimated by incorporating the disturbance specification of equation 8.

Empirical Application

Data Sources

The model developed in the last section is used to formulate a price-forecasting model for the consumer prices of 16 food categories as defined in the structure of Consumer Price Indexes (CPI). These food categories are (1) beef and veal, (2) pork, (3) other meats, (4) poultry, (5) fish and seafood, (6) eggs, (7) dairy products, (8) fats and oils, (9) fresh fruits, (10) fresh vegetables, (11) processed fruits and vegetables, (12) sugar and sweets, (13) cereals and bakery products, (14) nonalcoholic beverages, (15) other prepared foods, and (16) food away from home. The price data for these food categories come from the annual *Consumer Price Index* from 1980 to 1997 (U.S. Department of Labor). Per capita total expenditures to represent the income variable are computed by dividing the personal consumption expenditures (obtained from the U.S. Department of Commerce) by the civilian population of 50 States on July 1 of each year.

The quantity data are compiled from *Food Consumption, Prices, and Expenditures* (Putnam and Allshouse, 1999). Most of the food quantities are measured in retail weight. For example, the quantities of red meats are measured in retail cut equivalent. The quantity of poultry is measured in boneless trimmed equivalent. The quantities of dairy products are measured in milk equivalent on milkfat basis. Some quantity data of food categories cannot be constructed to match the price indexes defined by the CPI. For example, wheat food use was tried as a quantity proxy in the equation for cereals and bakery products but was not satisfactory in fitting the demand equation. One reason is that wheat is only one farm-level ingredient in cereals and bakery products, so the farm-level quantity is probably not representative of the retail quantity. Another reason is that the farm value represented by the wheat quantity measure is a small share of the retail product value of cereals and bakery products.

Given the difficulty of defining a pairwise price-quantity for individual food categories, the aggregated quantities consisting of six food groups (red meats, poultry, dairy, fruits and vegetables, starchy foods, and other foods) are used as proxy explanatory variables for each price equation. These aggregate quantities for each food group are calculated as the Laspeyres indexes from a total of 143 individual food items. For explaining price changes of those food categories without explicitly defined quantities of own category as an explanatory variable in the model, cross-quantity effects and per capita income are considered major determinants. For example, the price variations of the other meats category are likely captured or represented by per capita income and the cross-quantity effects with red meats and poultry. Because the pairwise price-quantity is lacking for some food categories, the parametric constraints across demand equations (equation 7) cannot be applied, and each price equation of the demand system has to be estimated separately.

Estimation Results

The estimation results by applying an autoregressive procedure (equation 8) with a specification of residuals lagged up to 2 years are contained in table 1. The quantity variables of food groups, the lagged residuals, and a constant term are listed across the top of the table, and the normalized price variables defined as the consumer prices deflated by the index of per capita income are listed down the left-hand side. For each pair of estimates, the upper part is the estimated price flexibility of a particular food category in response to the changes in group quantities, and the lower part is the estimated standard error.

In table 1, the estimated price flexibilities in each column can be used to assess how a change in the quantity of a specific food group, while holding the quantities of other groups fixed, affects the changes of all food prices. According to the estimates, for example, a marginal 1-percent increase in the quantity of red meats would reduce beef prices by 0.91 percent, pork prices by 1.42 percent, and prices of other meats by 0.27 percent. On the other hand, a marginal 1-percent increase in the quantity of poultry would reduce poultry prices by 0.84 percent.

Regarding the cross-quantity effects, an estimated cross-price flexibility between two food categories shows the percentage change in the amount consumers are willing to pay for one food when the quantity of another food increases by 1 percent. A negative cross-price flexibility means substitution, while a positive sign signals a complementary relationship between the two goods. This is because a marginal increase of the quantity of one good may have a substitution effect on other goods, and the price of other goods should be lower to induce consumers to purchase the same quantity of the other goods. For similar reasons, a positive cross-price flexibility means a complementary relationship.

Table 1—Estimated price flexibilities, 1980-97

Food	Quantity						A(1)	A(2)	Const.	R^2	D.W
category	R.meat	Poultry	Dairy	Fru-veg	Starch	Other					
Price											
Beef	-0.9103	-0.1463	0.9731	-2.228	0.3930	-1.5542	-0.1730	0.8288	19.7644	0.98	2.25
	0.5804	0.3875	0.7832	0.5998	0.4629	0.6856	0.2282	0.1901	3.7322		
Pork	-1.4213	-1.0333	0.2833	-0.5971	0.4137	-0.2665	0.0083	0.7127	15.6813	0.98	2.19
	0.5191	0.3363	0.6111	0.4300	0.3796	0.5373	0.2854	0.2570	3.1171		
O. meat	-0.2662	-0.4173	0.2760	-1.5301	0.7003	-1.0070	0.2346	0.7306	14.0854	0.99	2.25
	0.4562	0.2646	0.4570	0.2948	0.2628	0.4266	0.2830	0.2495	2.5691		
Poultry	-0.3992	-0.8367	1.3397	0.3317	0.6789	-1.8243	0.0456	0.7690	6.9754	0.98	1.81
	0.6098	0.3930	0.7266	0.4974	0.4353	0.6241	0.2672	0.1976	3.5818		
Fish	0.4006	-0.9340	3.6906	1.4430	1.7932	-3.8765	0.9194	0.5765	-7.7412	0.96	2.41
	0.4645	0.2361	0.4219	0.2293	0.2171	0.4154	0.2796	0.2835	2.6863		
Eggs	-1.6583	0.4597	-4.6023	-0.9403	-1.8582	0.8445	0.2614	0.4717	38.7187	0.95	2.05
	1.5750	0.8698	1.6411	1.0972	0.8885	1.6114	0.3579	0.3622	9.3285		
Dairy	-0.1783	-0.0538	-0.8482	-1.5566	-0.1226	-0.3093	0.8725	0.6772	17.7182	0.99	2.24
	0.5139	0.2434	0.5009	0.2309	0.2180	0.4824	0.3404	0.3819	3.1305		
Fat-oil	-0.2304	-0.0820	0.4172	-1.1413	-0.4135	-0.6658	0.2503	0.9355	13.3481	0.99	1.77
	0.2740	0.1571	0.2823	0.1854	0.1603	0.2579	0.1550	0.0782	1.5532		
Fruits	-1.9234	-0.6129	-0.4895	-1.0900	0.8372	0.8228	0.1439	0.7708	14.6914	0.91	1.84
	0.6464	0.3728	0.6130	0.4234	0.3618	0.6043	0.2185	0.2307	3.5118		
Veget.	0.8952	0.7380	-1.8528	0.0539	-0.0475	-0.8965	1.0257	0.8455	8.3168	0.94	1.53
	0.3616	0.1752	0.3180	0.1641	0.1536	0.3221	0.1930	0.1727	2.0949		
Pro. F&V	-0.5765	0.0285	0.3798	-0.0196	-0.8083	-1.3045	0.8989	0.5559	14.0099	0.99	2.57
	0.3625	0.1837	0.3714	0.1880	0.1791	0.3426	0.2909	0.3090	2.1740		
Sugar	0.1189	-0.3436	0.6003	-1.0903	0.2854	-0.8623	-0.0094	0.8353	9.6658	0.99	2.20
	0.3157	0.1978	0.3910	0.2766	0.2256	0.3394	0.2610	0.2039	1.9273		
Cereal	0.6012	0.4581	-1.2757	-1.2137	-0.1140	0.0186	0.5964	0.4646	10.4283	0.98	2.11
	0.4674	0.2260	0.3329	0.1852	0.1704	0.3677	0.3855	0.4477	2.5367		
Beverage	0.1991	-1.3034	-0.0354	-0.4102	0.9869	-0.2275	0.7213	0.6979	7.4882	0.99	2.03
	0.3253	0.1644	0.2756	0.1587	0.1412	0.2909	0.2574	0.2801	1.8378		
Pre. food	-0.1502	-0.2142	-0.1900	-0.4653	-0.0003	-0.5002 -	0.3165	0.1613	10.4945	0.99	2.11
	0.2832	0.1817	0.4107	0.2908	0.2388	0.3686	0.3595	0.3671	2.1118		
Food away	-0.1099	-0.2759	0.5666	-0.5129	-0.1798	-0.3626	-0.6332	0.5804	7.5716	0.99	2.37
	0.1854	0.1759	0.3012	0.3203	0.2185	0.3318	0.3317	0.3343	1.5418		

Note: For each pair of estimates: the upper part is flexibility, and the lower part is standard error.
The notations are R. meat (red meats), Fru-veg (fruits and vegetables), Starch (starchy foods), Const.(constant), O. meat (other meats), Veget. (fresh vegetables), Pro. F&V (processed fruits and vegetables), and Pre. food (prepared foods). A(1) and A(2) represent the autoregressive residuals lagged by 1 and 2 years, respectively, and D.W. represents Durbin-Watson statistics.

According to the estimates in table 1, for example, the cross-price flexibility of poultry with respect to the quantity change of red meats is -0.40 percent, and the cross-price flexibilities of beef, pork, and other meats with respect to the quantity change of poultry are -0.15, -1.03, and -0.42 percent. The negative values of these cross-price flexibilities suggest that red meats and poultry are substitutes. Many of the estimated cross-price flexibilities, however, are not statistically significant. This is probably because even though some individual foods either substitute or complement, aggregating different food items into a food category mitigates these cross-quantity effects. Also, annual data aggregates over seasons may contribute to the lack of statistical significance in some estimated cross-price flexibilities.

In addition, the residuals of the demand system are further specified as a second-order autoregressive process as suggested in equation 8. The estimation results are presented in the table under the columns of A(1) and A(2), which are estimated coefficients of autoregressive residuals lagged by 1 and 2 years, respectively. The estimates of goodness of fit (R^2) in each price equation are satisfactory. All estimates of R^2 are higher than 0.91, and in 14 of 16 cases the R^2 is higher than 0.95. The Durbin-Watson (D.W.) statistics shown in the last column of the table suggest that the errors of each price equation are not serial correlated, and the estimated standard error is unbiased for use in a significant test of estimated price flexibilities.

To examine the possibility of improving forecasting performance by applying the autoregressive procedure (AUTO) rather than ordinary least squares (OLS), two indicators of performance are presented in table 2; one is R^2 and the other is the root-mean-square percent error (*RMSE*). The *RMSE* of the *ex post* simulation is calculated as

$$RMSE = [\, \Sigma_t (p_t - p_t^*)^2 / T \,]^{1/2} \; / \; p \times 100 \qquad t = 1,2,..,T \tag{9}$$

where p_t and p_t* are respectively the actual and fitted normalized price levels for a sample period *T* years, and *p* is an average of actual normalized price levels. The *RMSE* expressed as a percent error of sample mean can be used for comparison across the price equations, because each *RMSE* is independent of the magnitude of each price index series, which ranged from 130 percent for nonalcoholic beverages to 236 percent for fresh fruits in 1997.

According to the estimated indicators in table 2, the estimates of R^2 in the AUTO case are uniformly higher than those of OLS, especially for cases like fresh fruits, which increased from 0.81 to 0.91, and fresh vegetables, which increased from 0.74 to 0.94. Regarding estimated *RMSE*s, most of the estimates of AUTO are smaller than those of OLS, except for cereal and other prepared food categories with slightly higher estimates. The measures of *RMSE* for the AUTO model range between 0.37 and 1.98 percent, while the measures for the OLS model range between 0.38 and 2.03 percent.

On the basis of estimated R^2 and *RMSE*, as expected, the application of an autoregressive model yields significant improvement in forecasting performance. The conformity of the fitted prices with the sample observations by using the AUTO model appears reasonably good. These results provide evidence that the estimated parameters adequately reflect food price responses to changes in quantity and income over the sample period. Therefore, for the purpose of price forecasting, the estimates of the autoregression model contained in table 1 should be used.

To clarify the forecasting results over the sample period, the fitted normalized prices from the estimated model are further transformed into Consumer Price Indexes. To get a close look at the accuracy of fitted prices, a comparison of actual and fitted food prices over the years 1995, 1996, and 1997 are presented in table 3. The errors of prediction are within 5 percent for most cases; in particular, all the errors of prediction in 1997 are within 3 percent. In addition, the turning-point errors over the whole sample period 1980-97 are listed in the last column of the table. The number of turning-point errors among 17 observed changes is equal to 5 errors or less in 13 cases out of 16 price forecasts. Graphic comparisons of actual and fitted results are presented in appendix A. This graphic presentation provides additional information about forecasting performance.

To facilitate the application of the price-forecasting model, a spreadsheet model was developed for an automated simulation of food prices. Users are required to provide input data about the concerned per capita quantity of food consumption and per capita income. The simulation results expressed in logs of normalized prices that is $\log(p_{i\,t} / m_t)$ at year *t*, are generated first. Then all forecasts of normalized prices are transformed into price index levels.

Table 2—Comparison of autoregressive and ordinary least square results

Food category	R^2		RMSE	
	AUTO	OLS	AUTO	OLS
Beef and veal	0.98	0.97	0.99	1.31
Pork	0.98	0.98	0.76	0.80
Other meats	0.99	0.99	0.60	0.73
Poultry	0.98	0.96	0.90	1.08
Fish and seafood	0.96	0.94	0.63	0.72
Eggs	0.95	0.94	1.98	2.03
Dairy products	0.99	0.99	0.65	0.78
Fats and oils	0.99	0.99	0.40	0.76
Fresh fruits	0.91	0.81	0.74	0.97
Fresh vegetables	0.94	0.74	0.50	0.92
Pro. fruit & veget.	0.99	0.98	0.52	0.69
Sugar and sweets	0.99	0.99	0.49	0.66
Cereals and bakery	0.98	0.98	0.42	0.40
Beverages	0.99	0.99	0.41	0.52
Prepared foods	0.99	0.99	0.43	0.40
Food away from home	0.99	0.99	0.37	0.38

Note: The notations are R^2 (R-squared), *RMSE* (root-mean-square percent error), AUTO (autoregressive procedure), and OLS (ordinary least squares).

Table 3—Forecasting performance

Food category	1995 Actual (1)	1995 Predict (2)	1995 Error percent	1996 Actual (1)	1996 Predict (2)	1996 Error percent	1997 Actual (1)	1997 Predict (2)	1997 Error percent	Turning point error
Beef	134.9	133.0	-1.39	134.5	140.1	4.15	136.8	137.6	0.56	3
Pork	134.8	140.1	3.90	148.2	145.7	-1.70	155.9	155.4	-0.31	1
O. meat	139.0	140.5	1.06	144.0	145.3	0.94	148.1	146.1	-1.36	2
Poultry	143.5	142.8	-0.46	152.4	150.9	-0.98	156.6	157.2	0.36	7
Fish	171.6	159.9	-6.83	173.1	181.2	4.70	177.1	176.6	-0.28	4
Eggs	120.5	131.7	9.31	142.1	127.2	-10.46	140.0	144.1	2.92	4
Dairy	132.8	138.2	4.04	142.1	138.8	-2.31	145.5	144.3	-0.80	6
Fat-oil	137.3	138.5	0.89	140.5	140.5	-0.02	141.7	140.5	-0.81	4
Fruits	219.0	223.1	1.88	234.4	232.3	-0.88	236.3	234.9	-0.60	1
Veget.	193.1	185.6	-3.87	189.2	194.7	2.93	194.6	193.3	-0.65	5
Pro. F&V	137.5	139.9	1.76	144.4	142.7	-1.17	147.9	148.7	0.54	7
Sugar	137.5	138.9	1.00	143.7	144.7	0.70	147.8	146.0	-1.19	3
Cereal	167.5	170.8	1.95	174.0	171.6	-1.36	177.6	177.7	0.06	0
Beverage	131.7	130.8	-0.65	128.6	131.2	2.02	133.4	130.6	-2.12	5
Pre. food	151.1	151.3	0.13	156.2	155.8	-0.29	161.2	162.1	0.57	1
Food away	149.0	149.5	0.31	152.7	155.6	1.88	157.0	159.5	1.57	1

Note: The notations are O. meat (other meats), Veget. (fresh vegetables), Pro. F&V (processed fruits and vegetables), and Pre. food (prepared foods). Error percent is calculated as [(2) - (1)] / (1) x 100.

Concluding Remarks

In this study, an inverse demand system approach is applied to specify a price-forecasting model. Six aggregate food quantities and per capita income are used as explanatory variables for forecasting consumer price indexes of 16 food categories. To enhance the forecasting capacity of the model, the disturbance terms of each price equation are specified as a second-order autoregressive process. The forecasting performance of the model is satisfactory.

This price-forecasting model is useful in capturing economic demand-pull factors such as food use and income in the food price changes. The model, however, has its limitations and should be used in conjunction with some other food price-forecasting models. First, the accuracy of food price forecasts in this model is conditional on the prior information of aggregate food quantities and per capita income, while reliable prior information for these input data may be difficult to obtain. Second, the price-forecasting model developed here is an annual model, and some research is needed to extend the model for providing monthly or quarterly short-term price forecasts.

References

Box, G.E.P., and G.M. Jenkins. *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day, Inc., 1970.

Hicks, J.R. *A Revision of Demand Theory*. Oxford: Oxford Univ. Press, 1956.

Houck, J.P. "A Look at Flexibilities and Elasticities." *J. Farm Econ*., Vol. 48, May 1966, pp. 225-232.

Huang, K.S. *U.S. Demand for Food: A Complete System of Quantity Effects on Prices*, Technical Bulletin No. 1795, U.S. Dept. Agr., Econ. Res. Serv., July 1991.

Huang, K.S. "A Further Look at Flexibilities and Elasticities." *Amer. J. Agr. Econ*., Vol. 76, May 1994, pp. 313-317.

Muth, J.F. "Rational Expectations and Theory of Price Movements," *Econometrica*, Vol. 29, 1961, pp. 315-335.

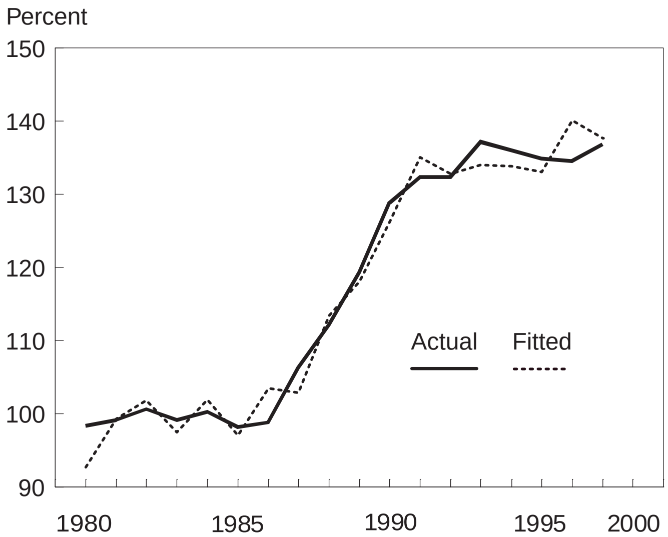
Putnam, J.J., and J.E. Allshouse. *Food Consumption, Prices, and Expenditures, 1970-97*. Statistical Bulletin No. 965. U.S. Dept. Agr., Econ. Res. Serv., April 1999.

U.S. Department of Commerce, *Personal Consumption Expenditures*, various issues.

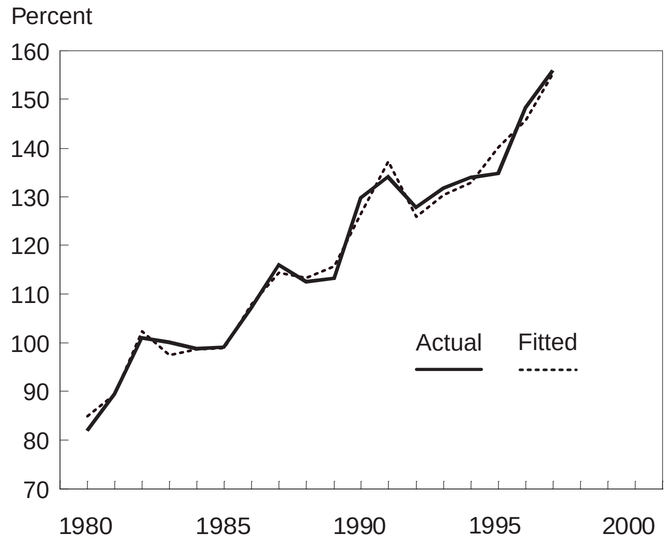
U.S. Department of Labor, *Consumer Price Index*, various issues.

Appendix A: Graphic comparison of actual and fitted food prices

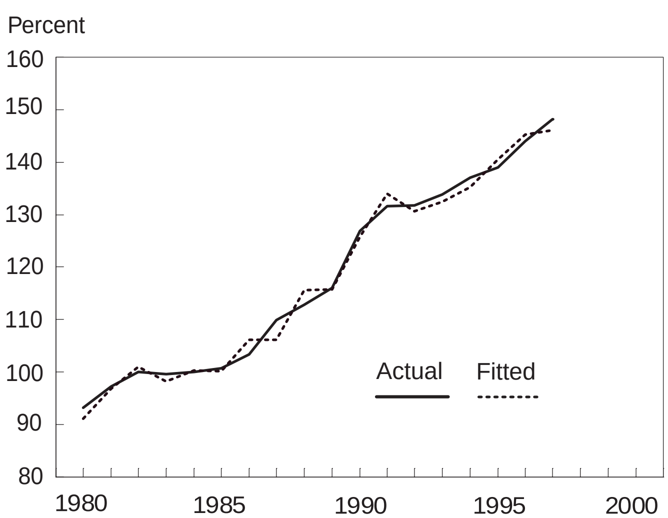
A-1: Consumer Price Index: Beef and veal
1982-84 = 100



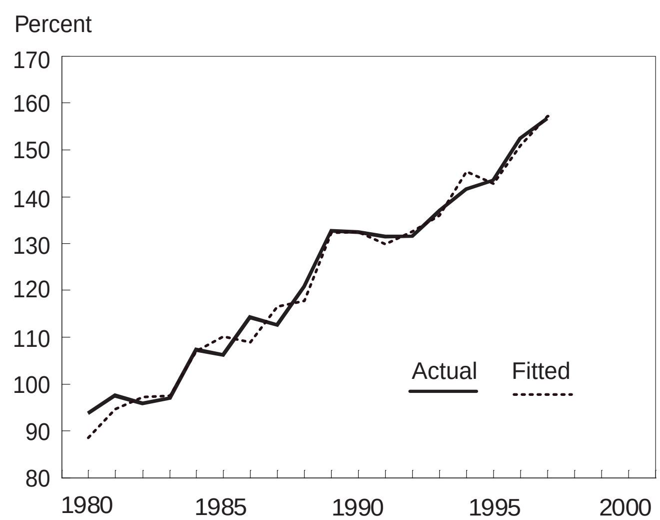
A-2: Consumer Price Index: Pork
1982-84 = 100



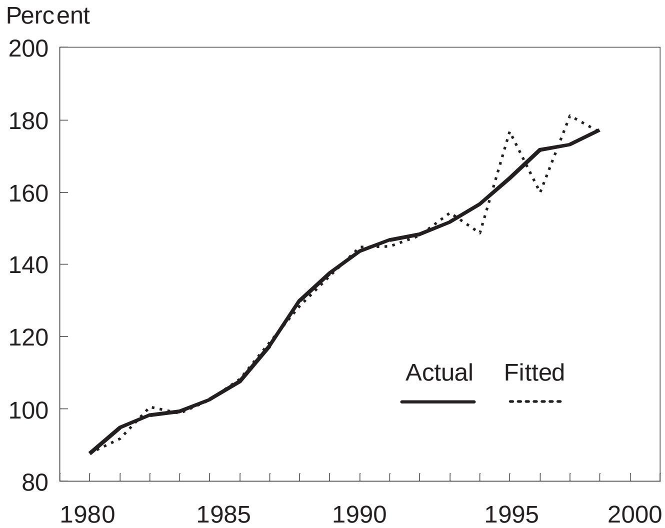
A-3: Consumer Price Index: Other meats
1982-82 = 100



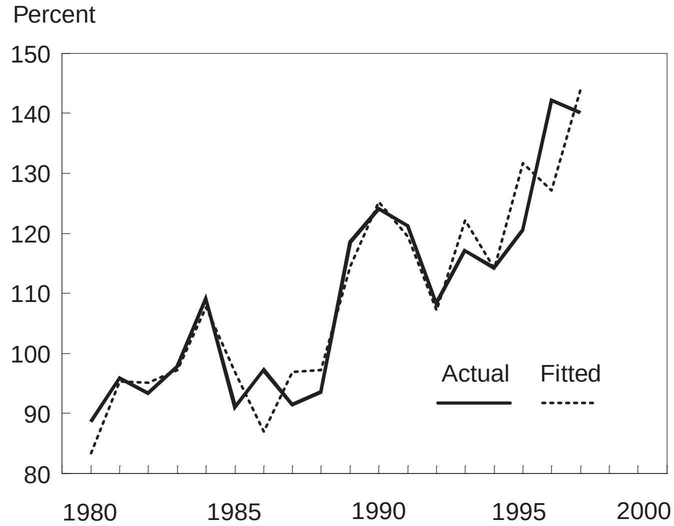
A-4: Consumer Price Index: Poultry
1982-84 = 100



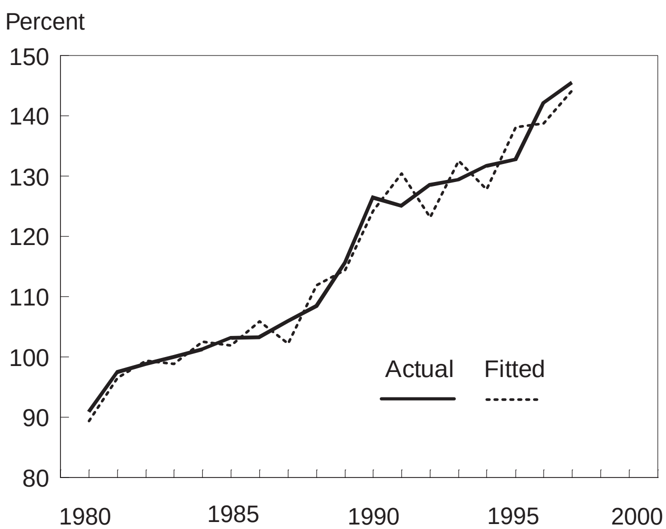
A-5: Consumer Price Index: Fish and seafood
1982-84 = 100



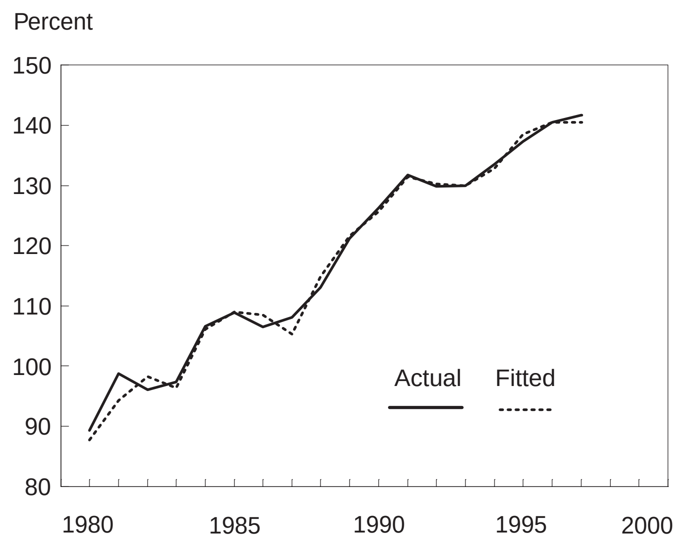
A-6: Consumer Price Index: Eggs
1982-84 = 100



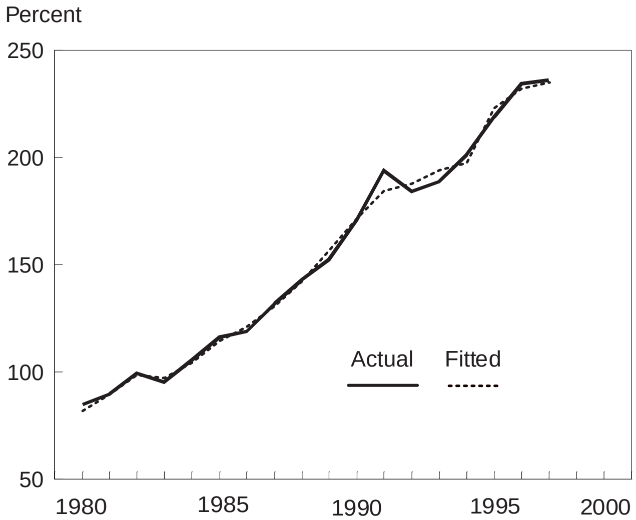
A-7: Consumer Price Index: Dairy products
1982-84 = 100



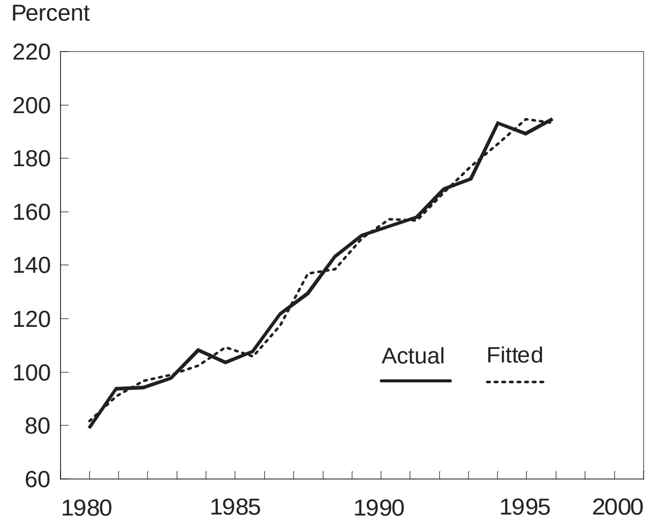
A-8: Consumer Price Index: Fats and oils
1982-84 = 100



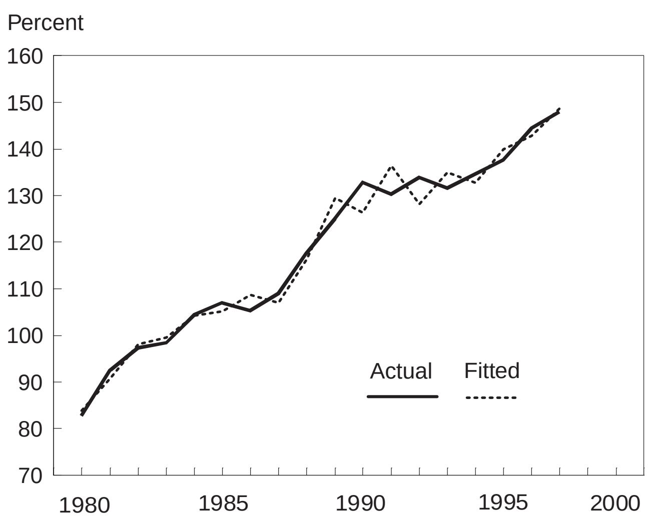
A-9: Consumer Price Index: Fresh fruits
1982-84 = 100



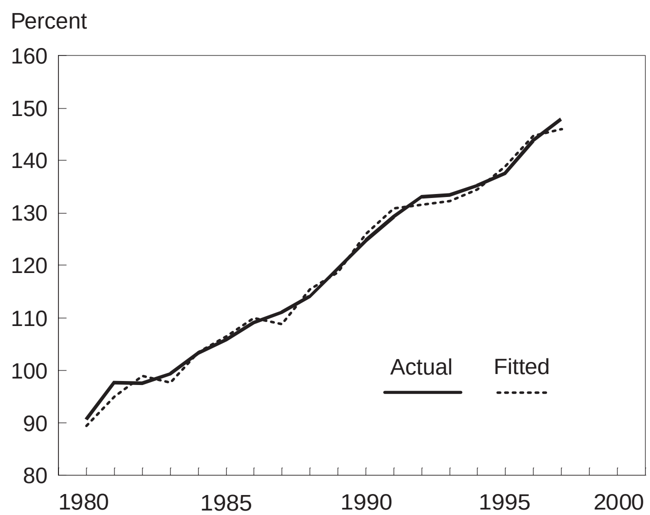
A-10: Consumer Price Index: Fresh vegetables
1982-84 = 100



A-11: Consumer Price Index: Processed fruits and vegetables
1982-84 = 100

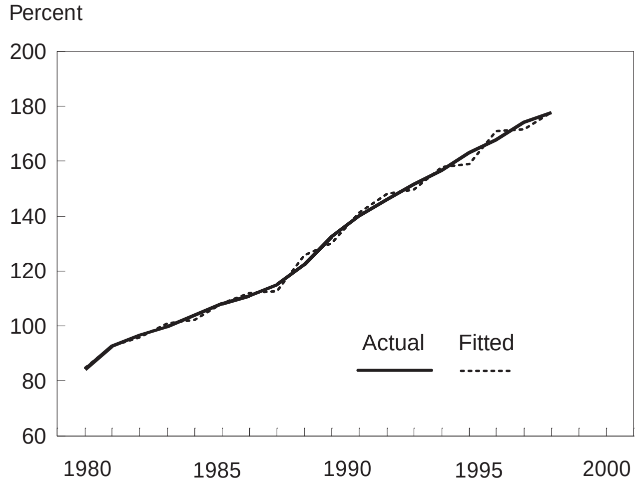


A-12: Consumer Price Index: Sugar and sweets
1982-84 = 100



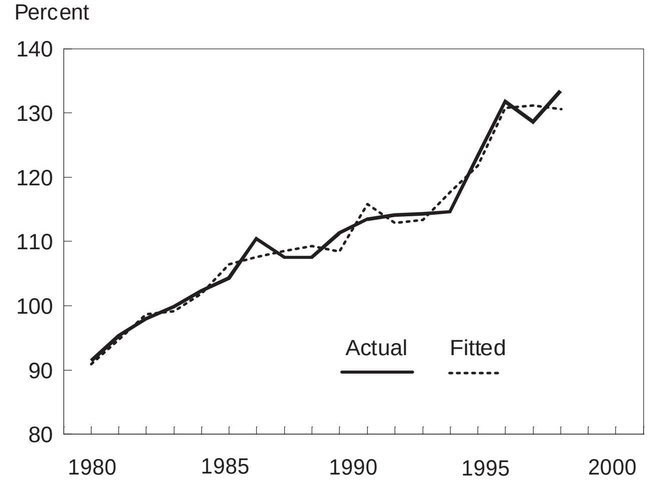
A-13: Consumer Price Index: Cereal and bakery Products

1982-84 = 100



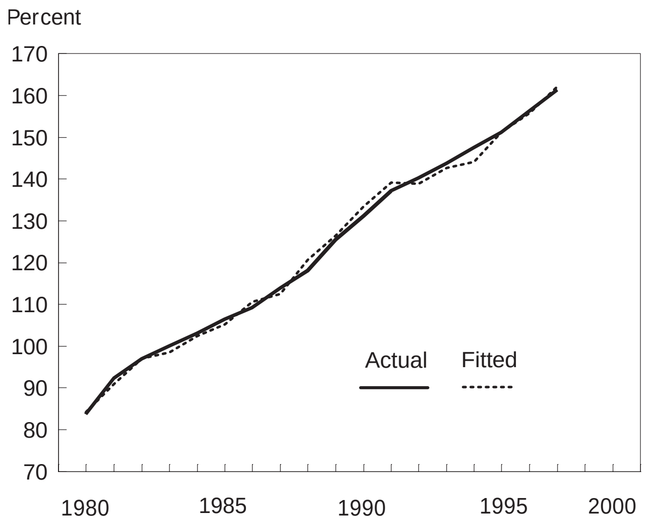
A-14: Consumer Price Index: Non-alcoholic beverages

1982-84 = 100



A-15: Consumer Price Index: Other prepared foods

1982-84 = 100



A-16: Consumer Price Index: Food away from home

1982-84 = 100